A Seasonal Regularity in the Impact of Investor Sentiment on Asset Prices

By

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Abstract

We explore whether sentiment-induced mispricing and the subsequent speed of correction is affected by investor mood, as measured by the seasonal onset of depression (or winter blues). Using a measure of negative sentiment based on households' internet searches, we first find that investors do not make sentiment-induced-mispricing errors near the spring equinox, during which people are recovering from seasonal depression symptoms. Second, we find the correction speed of mispricing in equity returns in the two days after the negative sentiment shock in the fall is not different from the correction speed in the summer. Lastly, we tease out known risk factors from the FEARS index and find that the orthogonalized FEARS index no longer explains contemporaneous returns, but continues to predict positive returns in the next two days. Moreover, we identify an insignificant seasonality pattern in the predictability of the orthogonalized FEARS index.

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"The Market price reflects not only the differing value opinions of many orthodox security appraisers, but also all the hopes and fears and guesses and moods, rational and irrational, of hundreds of potential buyers and sellers" (Robert Edwards and John Magee, Technical Analysis of Stock Trends, page 5, 1948).

Introduction

In the paper, we document a seasonal difference in mispricing as well as a seasonal mispricing correction pattern in equity returns. This pattern is economically and statistically significant. In our paper, mispricing is a pattern in which equity returns are high after experiencing negative sentiment shocks. The sentiment-induced mispricing is completely reversed after two days in the fall, when more people suffer from Seasonal Affective Disorder (SAD). However, the sentiment-induced return reversal is not significant in the spring, when people tend to recover from seasonal depression symptoms.

A large body of literature explores the forecasting power of sentiment. For example, Baker and Wurgler (2006) find that high aggregate market sentiment predicts low future returns of hard-to-arbitrage stocks. Edmans, Garcia, and Norili (2007) document a next-day abnormal negative return on the market index following soccer team defeats. Researchers interpret sentiment-induced return reversals as a correction for mispricing (see, for example, de Bondt and Thaler, 1985 and 1987; Baker and Wurgler, 2006; Da, Engelberg, and Gao, 2015). Moreover, a seasonal pattern is documented in financial asset returns. Jordan and Jordan (1991) find seasonal patterns in daily bond returns. Kamstra, Kramer, and Levi (2003, 2015) document SAD as the source of seasonal variation in various asset-class returns. They postulate that SAD affects investors' risk attitudes and their corresponding investment decisions, and these, in turn, move the market.

However, there is still a gap in the literature, namely whether the mispricing correction of sentiment-induced returns exhibits a seasonal pattern. In the paper, we investigate this question. Our search for seasonal patterns is motivated by findings in the psychology literature which document that mood influences individuals' cognitive processes (for a comprehensive review of this literature, see Gendolla, 2000). Positive mood leads people to adopt simple information processing strategies based on heuristics, whereas individuals experiencing a negative mood tend to process information analytically (see, for example, Schwarz and Clore, 2003). Thus, we conjecture that the speed of sentiment-induced mispricing correction is correlated with investors' moods. Specifically, the adoption of more rigorous analytical information processing methods when mood is negative may lead to improved investor ability to separate fundamental information and sentiment noise.

This paper examines the sentiment-induced mispricing as well as mispricing correction pattern by using the index known as the Financial and Economic Attitudes Revealed by Search (FEARS), a market-sentiment index developed by Da, Engelberg, and Gao (2015), together with an $Onset$ variable provided by Kamstra, Kramer and Levi (2015), which measures the change in the proportion of people actively experiencing SAD symptoms. Da, Engelberg, and Gao (2015) find that FEARS is correlated with same-day low U.S. equity returns and with high returns the following day. Kamstra, Kramer and Levi (2015) find that the value of $Onset$ is high near the fall equinox and low near the spring equinox.

We present six results. First, the effect of negative sentiment (high FEARS) on equity returns vanishes in the spring (low value of $Onset$). Second, the negative contemporaneous correlation between negative sentiment shock and stock market does not vary across seasons. Third, in the following two days, the absolute recovery is higher in the fall than in the summer. In other words, the returns are more positively sensitive to negative sentiment in the high regime of $Onset$. Fourth, if we measure the speed of correction as ratio, the magnitude of recovery on day $t + 1$ expressed as a percentage of decline on day t, then the correction speed is not statistically different from each other between fall and summer. Fifth, if we tease out the known-risk factors from the sentiment index, the orthogonalized sentiment index can no longer explain negative contemporaneous returns. The market factor wins the tug-of-war with the FEARS index. However, it can still predict positive returns in the next following two days. Finally, the orthogonalized sentiment index exhibits no significant seasonal pattern in the predictability of equity returns.

This paper, to the best of our knowledge, is the first one to study seasonal patterns in sentiment-induced mispricing as well as the mispricing correction. We investigate the relationship between the information-processing effect of SAD and FEARS-induced mispricing reflected in market returns. We show that investors' mood (as measured by $Onset$) affects how market sentiment moves market returns.

Related literature and hypothesis development

Prior research has investigated how sentiment affects prices in the stock market. For example, using opinion-based survey data, Fisher and Statman (2000) find that the sentiments of both individual and institutional investors are negatively correlated with future S&P 500 returns, but Clarke and Statman (1998) fail to find a similar result for financial newsletter writers. A central prediction of sentiment is return reversal. Sentiment is documented to be positively correlated with contemporaneous market returns (Lee, Jiang, and Indro, 2002; Brown and Cliff, 2004; Tetlock, 2007; Edmans, Garcia and Norli, 2007), negatively correlated with future market returns (Wang, 2003; Fisher and Statman, 2003; Brown and Cliff, 2005; Baker and Wurgler, 2006, Bollen, Mao and Zeng, 2011; Kim, Ryu and Seo, 2014; Garcia, 2013), or both (Kaplanski and Levy, 2009; Da, Engelberg and Gao, 2014). Researchers usually interpret the return reversal pattern as a sentiment-induced mispricing correction.

Market sentiment is usually quantified in three ways. The first measurement is opinion-based survey indices such as the Index of Consumer Sentiment from the University of Michigan, and the Investor Intelligence Survey and the Consumer Confidence Survey from the Conference Board. One potential shortcoming is that surveys may not reveal respondents' real attitudes. The second measurement approach uses a sentiment proxy which is a composite index created using a principal component analysis approach such as the Baker and Wurgler sentiment index (Baker and Wurgler, 2006).[1] The disadvantage of this empirical approach is that the sentiment proxy may be contaminated by non-sentiment information such as macroeconomic conditions. The third measurement approach is a web-based search on sentiment such as Financial and

[1] Using principal components analysis, Baker and Wurgler (2006) form a sentiment index as a function of the closed-end fund discount, NYSE share turnover, the number of IPOs, the average first-day returns, the equity shares in new issues, and the dividend premium.

Economic Attitudes Revealed by Search (FEARS) index constructed by Google Trends (Da, Engelberg and Gao, 2014) and the Twitter Public mood index constructed by OpinionFinder (Bollen, Mao and Zeng, 2011). Moreover, Da, Ben-Rephael and Israelsen’s (2017) construct abnormal institutional investor attention index. They use news searching and news reading activity for specific stocks on Bloomberg terminals. The advantage of this approach is that data about investor sentiment lies in the availability of the daily frequency data of “revealed” investor preferences.

Sentiment here refers to aggregate pricing errors made by investors in the financial market. For instance, irrational exuberance during the high-tech bubble of the 1990s indicates that investors were unwarrantedly optimistic. An individual’s mood is described as a long-lasting affective state (see, for example, Batson, Shaw, and Oleson, 1992; Morris, 1992). Examples of factors affecting mood include illumination and light levels (see, Veitch, Gifford, and Hine, 1991; Barson, Rea and Daniels, 1992), the weather or seasonal sunlight exposure patterns (see, Schwarz and Clore, 1983; Eastman, 1990; Eagles, 1994), and the pleasantness of the environment (Schwarz, Strack, Kommer & Wagner, 1987).

Combined with evidence of seasonal variation in security returns, SAD has been identified as the source of the seasonal return effects (see, Kamstra, Kramer and Levi, 2003, 2015). SAD, correlated with the hours of daylight and temperature, is a condition of clinical depression (Molin, Mellerup, Bolvig, Scheike, and Dam, 1996; Magnusson, 2000). The existing literature has investigated how mood affects market returns (see, for example, Saunder, 1993; Hirshleifer and Shumway, 2003). In subsequent papers, Kamstra, Kramer and Levi (2003 and 2015) use SAD to explain seasonal cycles of both stock returns and treasury returns. They state that fewer hours of daylight induces a high degree of risk aversion which leads investors to shun risky assets and opt for safe investment alternatives such as treasury securities.

This paper is different from existing papers related to SAD. Instead of interpreting seasonal depression as a catalyst for time-varying risk aversion, our hypothesis is inspired by the psychology literatures on how mood influences cognitive processes. Several studies report that positive mood fosters a simplified heuristics-based information processing style in decision making (see the reviews of Gendolla, 2000; Schwarz and

Clore, 2003; and Forgas, 2002). On the other hand, negative mood induces agents to adopt an analytic, vigilant, and elaborate information-processing strategy (Schwarz, 1990; Bless, Bohner, Schwarz and Strack, 1990; Sinclair and Mark, 1995). Forgas and East (2008) find that negative mood also increases skepticism and improves the ability to detect deception. Bless Schwarz, Kemmelmeier (1996) find that people in a positive mood are more likely to make decisions based on stereotypes than are people in a negative mood (see, Bodenhausen, Kramer and Süsser,1994).

We add to the literature on sentiment-induced mispricing by examining the correlation between the $Onset$ of SAD and the magnitude of the mispricing, as well as the $Onset$ of SAD and the speed at which such mispricing disappear. Our main hypothesis is that at times of high $Onset$ of SAD (negative mood), investors reveal the fundamental (sentiment-free) asset value faster due to the tendency to adopt more rigorous analytical decision-making tools when negative mood looms. When individuals recover from SAD (low $Onset$), sentiment-induced pricing errors take longer to disappear due to the tendency of individuals to use heuristics when mood is positive. Although the existing psychology literature do not shed light on the magnitude of mispricing, we also speculate the level of mispricing may different across seasons.

FEARS, seasonal pattern, and asset returns

Our testing assets include the S&P 500 index and four highly liquid index exchange-traded funds (ETFs): SPDR S&P 500 (NYSEArca: SPY), PowerShares QQQ (NasdaqGM: QQQ), iShares Russell 1000 (NYSEArca: IWB), and iShares Russell 2000 (NYSEArca: IWM). Daily returns for these portfolios are taken from the Bloomberg database. In addition, we test our hypothesis using the CRSP equally-weighted and value-weighted portfolios. Table 1 displays summary statistics for the test assets.

[Insert Table 1 here]

The FEARS market sentiment index is from Joseph Engelberg's website.[2] The FEARS index measures aggregate investor sentiment with respect to the economic conditions of millions of households. This sentiment measure is revealed in individuals' internet-based word search. Specifically, to construct the FEARS index, the authors first select 149 "economic" words such as "Recession," "Gold," "Crisis," "Bankruptcy," and "Inflation Rate," which reveal either "positive" or "negative sentiment." Then they seek "top searchers" related to the above words. After removing insufficient observations and duplicates, the authors are left with 118 search terms. Next, the authors perform a rolling regression of adjusted daily log changes in selected search terms on market returns and choose the thirty terms with the most negative t-statistics. Finally, FEARS on day t is the average adjusted daily log changes of these thirty terms on day t. FEARS is measured daily from 2004/07/01 to 2011/12/30.

We obtain the daily measure of seasonally varying mood ($Onset$ variable), from Mark Kamstra's website.[3] The $Onset$ variable reflects the change in the proportion of individuals actively experiencing seasonal depression in North America. Kamstra, Kramer and Levi (2015) constructed the $Onset$ variable in three steps. First, by using Lam's (1998) clinical sample at one-year horizon, they calculate an incidence monthly variable which describes the proportion of SAD-sufferers actively experiencing depression symptoms (the cumulative proportion of individuals who have been diagnosed with the onset of depression minus the cumulative proportion of individuals who have been diagnosed with full recovery). Second, they interpolate the monthly cumulative values to daily cumulative values. By using the length of night, they then produce a fitted daily cumulative value. Finally, the daily $Onset$ data is the change in the above instrumented incidence variable (rescaled by multiplying by 30). We emphasize that the $Onset$ variable is constructed under a spline function. Thus, it is not a random variable. The peak times for experiencing the onset of depression are September and October; March and April are the peak months for recovery.

[2] We thank Da, Engelberg, and Gao for making these data available. The data are available at http://rady.ucsd.edu/faculty/directory/engelberg/pub/portfolios/research.htm.

[3] We thank Mark Kamstra for providing these data. The data are available at http://markkamstra.com/data.html.

In addition, we use the Chicago Board of Exchange (CBOE) daily market volatility index (VIX), the economic policy uncertainty index (EPU), and the Aruoba-Diebold-Scotti business conditions index (ADS) as control variables. We obtain VIX from Wharton Research Data Services. The EPU is constructed by Baker, Bloom, and Davis (2013)[4] and the ADS is obtained from the Federal Reserve Bank of Philadelphia.[5] Table 2 provides the correlation coefficients of the predictors.

[Insert Table 2 here]

To investigate seasonal patterns in the speed of sentiment-mispricing corrections, we run the following regression:

$$return_{i,t+k} = \beta_0 + \beta_1 \times FEARS_t + \beta_2 \times Onset_t \times FEARS_t + \beta_3 \times Onset_t + \sum_n \gamma_n Control_{i,t}^n + u_{i,t+k}, (1)$$

where: $return_{i,t+k}$ is test asset i's return on day $t+k$, $FEARS_t$ is the market sentiment index revealed from millions of households in North America, and $Onset_t$ is a proxy for seasonally varying investors' mood. Following Da, Engelberg, and Gao's (2014) paper, our control variables include five lags of asset returns, changes in EPU, ADS, and VIX. In model (1), there are three predictors: two main effects ($Fears$ and $Onset$) and one interaction ($Onset \times Fears$). We depict $Onset$ as a moderator of $Fears$. To express the regression of returns on $Fears$ at varied levels of $Onset$, the regression equation (1) is rearranged:

$$return_{i,t+k} = \beta_0 + (\beta_1 + \beta_2 \times Onset_t) \times FEARS_t + \beta_3 \times Onset_t + \sum_n \gamma_n Control_{i,t}^n + u_{i,t+k}, (2)$$

[4] The data are available at https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.
[5] The data are available at http://www.policyuncertainty.com/us_daily.html.

Following Aiken and West (1991), we refer to $(\beta_1 + \beta_2 \times Onset_t)$ as marginal effect of $FEARS$ on returns conditioned on the value of $Onset$. In our case, the moderator $Onset$ is a continuous and non-random variable. Cohen and Cohen (1983) suggest that researchers use the high, medium, and low values of the moderator, corresponding to one standard deviation above the mean of the moderator, the mean of the moderator, and one standard deviation below the mean of the moderator. However, in the fall (the peak time of developing SAD), the value of $Onset$ is about two standard deviations above the mean. In the spring (the peak time of recovery from SAD), the value of $Onset$ is around two standard deviations below the mean. To better describe the seasonal effect, we analyze two standard deviations above and below the mean of $Onset$. Moreover, we also provide analysis on values within the full range of $Onset$.

[Insert Table 3 here]

In table 3, we first test model 1 using the Standard and Poor's 500 index as the dependent variable. When $k = 0$ (i.e., on day t), the negative and insignificant coefficient on the interaction term $(Onset \times Fears)$ in Panel A suggests the relation between $FEARS$ and contemporaneous return is not significantly affected by $Onset$. In Panel B, we examine the results based on three values of $Onset$: two standard deviations above the mean of $Onset$, the mean of $Onset$, and two standard deviations below the mean of $Onset$, representing high, medium, and low seasonal mood shifts, respectively. Column (1) shows that the marginal effect is significant for high and medium $Onset$ days. When $Onset$ is high (a high proportion of individuals are developing SAD), a standard deviation increase in $FEARS$ (lower sentiment) corresponds to a decline of 36.26 basis points (significant at the 5% level) in the contemporaneous daily S&P 500 index.[6] For medium Onset days (neutral mood shifts), one standard deviation in $FEARS$ results in a decline of 16.76 basis points (significant at the 1% level) in same-day S&P 500 daily returns. When Onset is low (positive mood shifts), a one standard deviation increase in $FEARS$ yields an increase of 2.73 basis points in contemporaneous S&P 500 daily returns,

[6] In our sample, the estimated standard deviation in the FEARS index is 0.3421. We multiply 0.3421 to -0.0106 (the value of simple slope on day t when taking high value of $Onset$) to get -36.26 basis points.

which is not significantly different from 0. This indicates that there is no significant mispricing when $Onset$ is low (in the spring).

Columns (2) to (4) of Table 3 suggest a return reversal (correction) pattern. We first look at column (2) in Panel A. The positive and significant interaction term ($Onset \times Fears$) suggests that there is a significant seasonal difference for the return over the first day after the shock in $FEARS$. Specifically, column (2) in Panel B suggests that when $Onset$ is high, medium, and low, a one standard deviation increase in $FEARS$ predicts an increase of 22.91 basis points (significant at the 5% level), an increase of 6.16 basis points (significant at the 10% level), and a decrease of 10.60 basis points (not significantly different from zero), respectively, on day t+1. The significant interaction term indicates that the absolute recovery value 22.91 basis points in the fall is statistically different from the value 6.16 basis points in the summer.

To compare the mispricing correction speed, we calculate the proportion of correction (i.e., correction speed) when $Onset$ is high and medium separately. We do not calculate the speed increment when $Onset$ is low because of the insignificance of marginal effects, suggesting there is no significant marginal effect of $FEARS$ and $Onset$ on returns in the spring. In the fall (high value of $Onset$), the correction speed is 63.21% (22.92/|-36.26|). However, in the summer (medium value of $Onset$), the speed increment is 36.75% (6.16/|-16.76|). To test whether the correction speed is higher in times of high $Onset$ than in medium $Onset$, we adopt the GMM approach (please see details in Appendix A). The test t-statistics is 0.7129, which suggests that the value 63.21%, the correction speed in the fall, is not significantly different from the value 36.75%, the correction speed in the summer.

We further look at column (4), which investigates the two-day cumulative asset return. Like the analysis on day 1 in column (2), the correction speed is 102.84% and 79.59% in the fall and summer, respectively, for the returns on the subsequent two days. The GMM approach suggests that the t-statistic for the correction speed test is only 0.5575, which indicates that the value 102.84% is not significantly different from the value 79.59%.

This finding rejects our hypothesis, which states that the speed of sentiment (FEARS) induced mispricing correction increases during the Onset of SAD (negative mood), when investors tend to use analytics to interpret information (Schwartz, 1990; Bless, Bohner, Schwarz, and Strack, 1990; and Sinclair and Mark, 1995).

[Insert Figure 1 here]

To better illustrate the marginal effect of $FEARS$ and $Onset$ on S&P 500 returns, we plot the marginal effects over the full range of $Onset$, from January to December. The solid blue line in Figure 1 represents the marginal effect on day 0, which is the sentiment-related mispricing error contemporaneous to the sentiment shock. The red dashed line represents the marginal effect on day 1. The green dotted line depicts the marginal effect on day 2, and the black dotted line depicts the cumulative impact over days 1 and 2. The correction pattern is the most salient near the fall equinox. This evidence supports our finding that the absolute recovery is larger in the fall than in other seasons. The pattern in the early spring seems counter intuitive. However, the marginal effect is not significantly different from 0 during the early spring (See Table 1 and Tables 1, 2, and 3 in the Appendix). In other words, there is no significance in either sentiment-induced mispricing or in the correction pattern when the value of $Onset$ is low. People in a good mood may be less influenced by sentiment (in terms of both the initial mispricing and the ensuing correction). Overall, we confirm that the absolute correction on the S&P 500 index increases over the first day after the negative sentiment shock in the fall. However, the correction speed in the fall is not statistically different from the correction speed in the summer.

[Insert Table 4 here]

In table 4, we examine six more equities. Across all assets, the first finding is that when the value of $Onset$ is low, the marginal effects are all insignificant. In other words, negative sentiment shocks do not have any effect on equity returns in the spring, let alone predicting a short-term return reversal pattern. A potential explanation is that during the peak recovery months, investors dismiss the negative news. Second, all tested assets confirm that there is no seasonal variation in the contemporaneous impact of $FEARS$ on equity returns. Third, all test assets, except QQQ, show that in the day following the negative sentiment shock, the absolute recovery in the fall is larger than in the summer. Fourth, we perform all the speed tests on those assets which have positive and significant interaction terms on day $t + 1$, or on days $t + 1$ and $t + 2$. None of the correction speed is higher in times of high $Onset$. Specifically, CRSP value-weighted, CRSP equal-weighted, and iShares Russell 2000 ETF (IWM) reject our main hypothesis over a two-day horizon. Moreover, the SPDR S&P 500 ETF and the iShares Russell 1000 ETF reject our main hypothesis over a one-day horizon.

Let us take IWM as an example. On day 0, a one standard deviation increase in $FEARS$ corresponds with a decline of 31.81 basis points (significant at the 5% level) and a decline of 15.13 basis points (significant at the 5% level) in contemporaneous daily IWM ETF return when $Onset$ is high and medium, respectively. The insignificant interaction term on day t indicates that sentiment error is not related to mood. We can say with confidence that the FEARS-induced mispricing level is similar in the fall (low seasonal mood) and the summer (high seasonal mood). On day $t + 1$, when $Onset$ is high and medium, respectively, a one standard deviation increase in $FEARS$ predicts an increase of 36.95 basis points (significant at the 1% level) and an increase of 7.87 basis points (significant at the 10% level). The significant and positive interaction term indicates that 36.95 basis points in the fall is statistically different from 7.87 basis points in the summer. The absolute recovery is larger in the fall. However, the correction speed over the first day is 116.16% in the fall and 46.69% in the summer. The speed test t-statistic is 0.7485. Thus, the value 116.16% is not statistically different from the value 46.69%. We cannot say the correction speed is faster in the fall than in another season.

The significant interaction term on day $t + 1$ and day $t + 2$ indicates that the correction is dependent on $Onset$. When $Onset$ is high and medium, respectively, a one standard deviation increase in $FEARS$ predicts an increase of 47.21 basis points (significant at the 5% level) and an increase of 14.71 basis points (significant at the 5% level). The correction speed over the first two days is 148.41% in the fall and 87.77% in the summer. And the t-statistic is only 0.7241. Overall, the IMW rejects our main hypothesis that the sentiment-induced mispricing correction speed is faster in the fall than in the summer.

[Insert Figure 2 here]

We also plot the marginal effects of these six test assets. Figure 2 depicts the marginal effect of $FEARS$ and $Onset$ on equity returns. Overall, Tables 3 and table 4 verify that FEARS predicts a seasonal pattern on short-term return reversal. In the spring, the peak season for recovery of SAD (low value of $Onset$), there exists no sentiment-induced mispricing. In the summer, the season filled with people in high mood, equity returns reveal a weaker reversal pattern than in the fall, which is the peak season for Onset of SAD (high value of $Onset$). In fact, the negative sentiment shocks induce a similar level of mispricing in both summer and fall. Overall, in Figure 2, the absolute recovery appears to be larger in the fall than in the summer. However, the speed test suggest that the correction speed in the fall is not statistically different from the speed in the summer.

FEARS, seasonal pattern, and limits to arbitrage

The debate on the cross-sectional structure of realized return is on going (Statman, 1999). Market efficiency proponents argue that characteristics such as book-to-market ratio, firm size, and past returns are proxies for fundamental risks (Fama and French, 1996; Carhart, 1997). However, proponents of behavioral finance argue that characteristics-revealed mispricing reflects sentiment risk, particularly overreaction (De Bondt and Thaler, 1985, Jegadeesh and Titman, 1993; Lakonishok, Shleifer, and Vishny, 1994). Baker and Wurgler (2006) suggest that sentiment affects the price of hard-to-value stocks more than easy-to-value stocks. They find that unprofitable stocks, non-dividend-paying stocks, high volatility stocks, young stocks, extreme growth stocks, and distress stocks are more sensitive to sentiment risk, even after controlling for three Fama-French factors and a momentum factor.

In addition, limits to arbitrage explains the cross-sectional returns that are different from what traditional asset pricing models predict. Shleifer and Vishny (1997) show that arbitrage is not efficient under extreme circumstances, when mispricing is worsened due to deepened noise trader sentiment (i.e., deepened noise trader misperceptions). They also argue that professional arbitrageurs, judged by their performance, may face capital constraints when managing another people's money. Baker and Wurger (2006, 2007) state that firms whose valuation are particularly subjective are difficult to arbitrage. The ability to quickly identify the mispricing is one key of a successful arbitrage. Firms with "unsafe" characteristics such as "non-profitable," "non-dividend," and "extremely high growth rates" are hard to value, and therefore hard to arbitrage. Furthermore, the high idiosyncratic risks (Wurgler and Zhuravskaya, 2002) and low liquidity of these firms make it costly to arbitrage (Pontiff, 1996; D'Avolio, 2002).

Da, Engelberg, and Gao (2014), motivated by the idea of limits to arbitrage, find a stronger reversal pattern among hard-to-arbitrage firms. Thus, we investigate the seasonal reversal pattern among hard-to-arbitrage firms. Following Da, Engelberg, and Gao (2014), we sort portfolios based on stock characteristics. We first analyze the high Scholes-William (1977) beta sorted portfolios and high total volatility sorted portfolios. We create decile portfolios, where high is defined as stocks in the top decile and low is defined as stocks in the bottom decile. CRSP provides both daily Scholes-William beta and total volatility of individual stocks traded on the NYSE and AMEX. We rebalance the portfolios each year by ranking the statistics at the end of the previous year. Then using two measurements, we examine the portfolios with high "downside" risks. Specifically, we calculate the "downside beta" (i.e., β_i^-) and "downside sigma" (i.e., δ_i^-) for individual's stocks as follows,

$$\beta_i^- = \frac{cov(r_i, r_m | r_m < \mu_m)}{var(r_m | r_m < \mu_m)}, (3)$$

$$\sigma_i^- = \sqrt{var(r_i | r_m < \mu_m)}, (4)$$

where r_i is the individual stock's return, r_m is the market return, and μ_m is the average market return. We rank the individual stocks on "downside beta" or "downside sigma" using the past year of daily returns, tracking daily portfolios over the next month, and rebalancing the portfolios at the end of the next month. To create decile portfolios, we ensure that a security have valid returns for at least forty trading days in the previous year.

[Insert Table 5 here]

In Table 5, the results for hard-to-arbitrage portfolios reject our main hypothesis. Let us first look at columns 1 and 2. On day t, sentiment has a negative contemporaneous effect on high beta portfolios. When $Onset$ takes the high, medium, and low value, respectively, a one standard deviation increase in $FEARS$ corresponds with a decrease of 49.61 basis points (significant at the 5% level), a decrease of 23.37 basis points (significant at the 1% level), and a decrease of 4.79 basis points (not statistically significant different from zero). However, the insignificant interaction term on day t indicates that sentiment effects are not seasonally and statistically different for high-beta portfolios. On days $t+1$ and $t+2$, $FEARS$ predicts a reversal among high-beta portfolios. When $Onset$ takes on high, medium, and low values, a one standard deviation increase in $FEARS$ is associated with an increase of 70.47 basis points (significant at the 5% level), an increase of 23.60 basis points (significant at the 1% level), and a decrease of 23.26 basis points (not statistically significant different from zero), respectively. The significant and positive interaction term indicates that 70.47 basis points in the fall is statistically different from 23.60 basis points in the summer. The absolute recovery is higher in the fall.

The correction speed over the next two days after the negative sentiment shock in the fall (high value of $Onset$) is 142.05% (70.47/|-49.61|) and is only 86.23% (23.60/|-27.37|) in the summer (medium value of $Onset$). The t-statistics for speed test is 0.7015, which suggest that our main hypothesis is rejected. The correction speed, 142.05%, in the fall is not statistically different from the speed, 86.23%, in the summer.

In addition, as shown in columns 1 and 2 in Panel B, the insignificant marginal effects when $Onset$ is low indicates that there is no sentiment effect in the spring. Similarly, from Panel B in column 3 and 4, the correction speed over the next two days among the high volatility stocks in the fall is 118.11% (51.32/|-43.45|) is not statistically different from the speed 80.41% (17.45/|-21.55|) in the summer. Moreover, the marginal effects are not different from zero when $Onset$ is low.

From column 1 to column 4 in Panel C of Table 5, our main conjecture is rejected again. For example, on day t, when $Onset$ takes the high, medium, and low value, respectively, a one standard deviation increase in $FEARS$ is associated with a decrease of

62.60 basis points (significant at the 5% level), a decrease of 30.10 basis points (significant at the 1% level), and an increase of 2.43 basis points (not statistically significant) in high downside beta portfolios. On days $t + 1$ and $t + 2$), the correction speed over the next two days in the fall (high value of $Onset$) is 125.14% and in the summer (medium value of $Onset$) is only 88.64%. However, the t-statistics of the speed test is only 0.6727. Again, the marginal effect of $FEARS$ are not significant different from zero during the spring (low value of $Onset$).

Overall, hard-to-arbitrage stocks reject our central hypothesis that the sentiment induced mispricing speed is stronger in the fall. We also explore the seasonal reversal pattern in easy-to-arbitrage portfolios.

[Insert Table 6 here]

In Table 6, we show that easy-to-arbitrage portfolios are less sensitive to sentiment relative to hard-to-arbitrage portfolios. First, we find that only low Scholes-William beta portfolios and low total volatility portfolios show a reversal pattern that is associated with $FEARS$. However, the reversal effects of $FEARS$ on easy-to-arbitrage portfolios are much smaller than they are for the hard-to-arbitrage portfolios. Moreover, contrary to the previous findings, we spot a seasonal pattern on day t instead of days $t + 1$ and $t + 2$. Let us take the low beta portfolios, in Panel B/column 1 and 2, as an example. On day t, when $Onset$ takes high, medium, and low values, respectively, a one standard deviation increase in $FEARS$ corresponds to a decrease of 23.26 basis points (significant at the 5% level), a decrease of 8.55 basis points (significant at the 1% level), and an increase of 6.16 basis points (not statistically significant). On days $t + 1$ and $t + 2$, when $Onset$ takes the high, medium, and low value, respectively, a one standard deviation increase in $FEARS$ is associated with an increase of 10.95 basis points (not statistically significant from zero), an increase of 4.79 basis points (significant at the 1% level), and a decrease of 15.39 basis points (not statistically significant). Since the (i.e., marginal effect) is only significant when $Onset$ takes the medium value, we cannot compare the correction speed among seasons. In other words, our main hypothesis that the correction speed is faster in the fall than in other seasons cannot be confirmed in easy-to-arbitrage portfolios.

Second, there is no reversal pattern associated with $FEARS$ in low downside beta portfolios and low downside volatility portfolios. Thus, our main hypothesis cannot be tested. We further investigate the seasonal reversal pattern in return spread between hard-to-arbitrage and easy-to-arbitrage portfolios (see Table 4 in the Appendix). We find the results on return spreads are similar to the results on hard-to-arbitrage portfolios. This finding is not surprising because the documented seasonal reversal pattern mainly comes from the hard-to-arbitrage portfolios.

FEARS and known rational risk factors

By construction, the $FEARS$ index is the average daily log changes in selected search items that have the most negative t-statistics when regressed on the market factor. To ensure that we focus on the noise content of $FEARS$, we tease out the proxies for rational pricing components of $FEARS$. We orthogonalize $FEARS$ with three well-known price factors (market factor, size factor, and book-to-market factor). To this end, we regress $FEARS$ on the Fama-French three factors, and take the residuals from the regression, which represents the noise content of $FEARS$.

To investigate the effect of the noise content of $FEARS$, we run the following regressions:

$$FEARS_t = \alpha_0 + \alpha_1 \times MKT_t + \alpha_2 \times HML_t + \alpha_3 \times SMB_t + \varepsilon_{FEARS,t}, (5)$$

$$return_{i,t+k} = \beta_0 + \beta_1 \times \varepsilon_{FEARS,t} + \sum_n \gamma_n Control_{i,t}^n + u_{i,t+k}, (6)$$

where: $FEARS$ is the sentiment index, MKT is the market factor, HML is the market-to-book factor, SMB is the size factor, ε_{FEARS} is the orthogonalized sentiment index, and $Control$ includes the control variables that we stated in section 3.

[Insert Table 7 here]

[Insert Table 8 here]

Table 7 shows the results for the SP500 index, CRSP value-weighted, CRSP equal-weighted, and four more highly traded ETFs as the dependent variable in equation (6). As we can see, on day t, the noise content of $FEARS$ does not correspond with contemporaneous equity returns. The point estimates of orthogonalized $FEARS$ are neither economically nor statistically significant. On days $t+1$ and $t+2$), we document the positive predictability of the orthogonalized $FEARS$ on equity returns. For example, a one-unit increase in the orthogonalized $FEARS$ can predict an increase of 41 basis points in the SP500 index. The test assets in Table 7 are highly correlated with the market returns. However, the construction of $FEARS$ is also correlated with the market factor. Thus, it is not surprising that after we orthogonalize $FEARS$with the market factor, the sentiment index cannot explain the contemporaneous market returns. We further test five industrial portfolios in Table 8. We confirm that the orthogonalized $FEARS$ index is not associated with the contemporaneous equity returns, but it can positively predict the returns of industrial portfolios.

[Insert Table 9 here]

Similar results can be obtained when we investigate the effect of the orthogonalized $FEARS$ index on the return spread between hard-to-arbitrage and easy-to-arbitrage portfolios in Table 9. Overall, after we tease out the rational pricing components from $FEARS$, the noise content is not associated with the contemporaneous negative equity returns, but it can predict positive returns in the next two days[7]. This is consistent with Baker and Wurgler's finding on predictability of sentiment. They find that low market sentiment predict high equity returns.

We further explore whether the predictability exhibits a seasonal pattern. We re-estimate regression (1) using the orthogonalized $FEARS$ index. Table 10 shows that we can only spot seasonality on the IWM ETF. In Table 11, only industry (2), which is the manufacturing, energy, and utilities industry, shows the seasonal pattern. In Table 12, we examine the hard-to-arbitrage portfolios, and we find a seasonal pattern in high total

[7] We test the orthogonalized FEARS effects on equity returns up to day $t+5$. However, the effects become insignificant after day $t+3$ in all test assets.

volatility portfolios and high downside beta portfolios. For example, in high total volatility portfolios, by $k = 2$ (i.e., on day $t + 1$ and day $t + 2$), when $Onset$ takes the high, medium, and low value, respectively, a unit increase in $FEARS$ is associated with an increase of 132 basis points (significant at the 5% level), an increase of 49 basis points (significant at the 1% level), and a decrease of 35 basis points (not statistically significant).

[Insert Table 10 here]

[Insert Table 11 here]

[Insert Table 12 here]

All in all, if we tease out the known pricing factors, the noise content of the $FEARS$ index cannot explain the contemporaneous equity returns. Instead, it can positively predict the equity returns and the cross-sectional equity returns in the following two days. Moreover, the predictability exhibits an insignificant seasonality pattern.

Conclusion

We first find that there is a significant seasonal correlation between $FEARS$ and equity returns. When fewer people suffer from SAD (low $Onset$, or in spring), the conditional effect of $FEARS$ on the contemporaneous return is tamed and is not significantly different from zero. In other words, investors do not make sentiment-induced errors in spring. Second, we did not find seasonal pattern on the contemporaneous impact of negative shocks on stock markets. Third, in the following two days after the negative sentiment shock, the absolute recovery is higher in the fall than in the summer. However, if we define the speed of correction as a ratio, then the results suggest that the sentiment induced correction speed in the fall is not statistically different from the speed in the summer. While previous studies demonstrate the impact of sentiment on asset returns and the impact of Onset on asset returns separately, the focus in the current study is on seasonal patterns in the speed of correction for sentiment-induced mispricing errors.

Lastly, we tease out the Fama-French three risk factors and explore the noise content of the $FEARS$ index. We find that the orthogonalized $FEARS$ index is not associated with contemporaneous returns, but it can predict positive returns in the following two days. This evidence suggests that the optimal portfolios exploit the predictability based on $FEARS$. The investors' holding components should be a function of $FEARS$. Moreover, we document limited seasonality patterns in the predictability of the orthogonalized $FEARS$ index.

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Table 1 Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Observation
S&P 500	1.5243e-04	0.0142	-0.0903	0.1158	1891
CRSP EW	4.6447e-04	0.0132	-0.0782	0.1074	1891
CRSP VW	2.7030e-04	0.0143	-0.0898	0.1149	1891
SPY	2.2909e-04	0.0141	-0.0984	0.1452	1891
QQQ	3.3965e-04	0.0147	-0.0896	0.1216	1891
IWB	2.3889e-04	0.0139	-0.0938	0.1137	1891
IWM	3.2878e-04	0.0179	-0.1124	0.0864	1891
FEARS	0.0017	0.3421	-2.2865	2.9236	1891
Onset	5.4544e-04	0.2130	-0.4333	0.4333	366
VIX	21.5183	10.9908	9.8900	80.8600	1891
EPU	104.1033	74.4110	7.4000	626.0300	1891
ADS	-0.4636	0.9871	-4.0647	0.9505	1891

This table shows summary statistics for the raw data used in this study. All data, except Onset, is from 2004/07/01 to 2011/12/30. S&P 500 is the S&P 500 index daily returns. CRSP EW is the CRSP daily returns on an equal-weighted portfolio. CRSP VW is the CRSP daily return on a value-weighted market portfolio. SPY, QQQ, IWB, IWM are daily returns from four highly liquid index exchange-traded funds. SPY, QQQ, IWB, IWM represents the SPDR S&P 500, the PowerShare QQQ, the iShares Russell 1000, and the iShares Russell 2000, respectively. FEARS is the sentiment index (see Da, Engelberg and Gao for details). Onset is the measurement of SAD (see Kamstra, Kramer and Levi for details). The Onset variable has only 366 observations because it is constructed using data from Lam (1998). VIX is the index of Chicago Board Options Exchange daily market volatility index. EPU is the economic policy uncertainty constructed by Baker, Bloom and Davis (2013). ADS is the Aruoba-Diebold-Scotti business conditions index.

Table 2 Correlation Coefficients of Predictors

	FEARS	FOI	Onset	VIX	ΔEPU	ΔADS
FEARS	1					
FOI	0.1349	1				
Onset	-0.0069	-0.0037	1			
VIX	0.0129	0.0126	0.0790	1		
ΔEPU	-0.0230	-0.0068	0.0167	-0.0118	1	
ΔADS	-0.0198	-0.0355	0.0203	0.0394	0.0241	1

This table shows the correlation coefficients of predictors used in this study. The sample period is from 2004/07/01 to 2011/12/30. FEARS is a sentiment index (for details see Da, Engelberg, and Gao, 2014). Onset is a measurement of SAD (see Kamstra, Kramer, and Levi for details). FOI is the interaction of FEARS and Onset. VIX is the Chicago Board of Exchange daily market volatility index. EPU is the economic policy uncertainty index constructed by Baker, Bloom, and Davis (2013). ADS is the Aruoba-Diebold-Scotti business conditions index. ΔEPU and ΔADS represent the daily changes in EPU and ADS, respectively.

Table 3 Sentiment, Seasonal Mispricing Correction Pattern, and S&P 500 returns

Panel A: FEARS, Onset and S&P 500 Index returns				
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
$constant$	0.0042***	-0.0002	0.0007426	5.1685e-05
	(0.0011)	(0.0010)	(0.0009)	(0.0018)
$Fears$	**-0.0049*** **	**0.0018***	0.0020**	**0.0039*** **
	(0.0016)	(0.00097)	(0.0010)	(0.0014)
$Fears \times Onset$	**-0.0134**	**0.0115***	0.0051	**0.0164**
	(0.0087)	(0.0064)	(0.0078)	(0.0105)
$Onset$	-3.8545e-04	-0.0011	-0.0011	-0.0022
	(0.0017)	(0.0016)	(0.0015)	(0.0029)
VIX	-1.8528e-04***	1.5837e-05	5.2888e-06	1.7296e-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔEPU	1.1243e-06	-1.3656e-05**	1.9105e-05**	5.0143e-06
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔADS	-0.0357	-0.0264	-0.0254	-0.0512
	(0.0315)	(0.0338)	(0.0317)	(0.0611)
$Ret(t)$		-0.1201***	-0.0590	-0.1777***
		(0.0372)	(0.0516)	(0.0559)
$Ret(t-1)$	-0.1570***	-0.0781	0.0391	-0.0406
	(0.0373)	(0.0517)	(0.0370)	(0.0598)
$Ret(t-2)$	-0.0911*	0.0142	-0.0177	-0.0036
	(0.0521)	(0.0367)	(0.0428)	(0.0520)
$Ret(t-3)$	0.0036	-0.0159	-0.0565	-0.0703
	(0.0357)	(0.0440)	(0.0447)	(0.0666)
$Ret(t-4)$	-0.0314***	-0.0520	0.0027	-0.0504
	(0.0425)	(0.0482)	(0.0482)	(0.0479)
$Ret(t-5)$	-0.0566***	-0.0036	-0.0341	-0.0342
	(0.0480)	(0.0443)	(0.0443)	(0.0647)
Observations	1891	1890	1889	1889
R^2	0.0665	0.0348	0.0200	0.0368
Panel B: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	**-0.0106*** **	**0.0067*** **	0.0042*	**0.0109*** **
	(0.0044)	(0.0030)	(0.0022)	(0.0051)
$Onset_M$	**-0.0049*** **	**0.0018***	0.0020**	**0.0039*** **
	(0.0016)	(0.00097)	(0.0010)	(0.0014)
$Onset_L$	**0.0008**	**-0.0031**	-0.0001	**-0.0031**
	(0.0037)	(0.0028)	(0.0031)	(0.0042)

Panel A represents estimates of the regression of the S&P 500 index daily returns over 0-2 days on the FEARS, Onset, and the interaction of FEARS and Onset. Specifically, Ret [t+1, t+2] is cumulative returns from day t+1 to day t+2. Panel B represents the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Figure 1 Marginal Effect of FEARS on S&P 500 returns

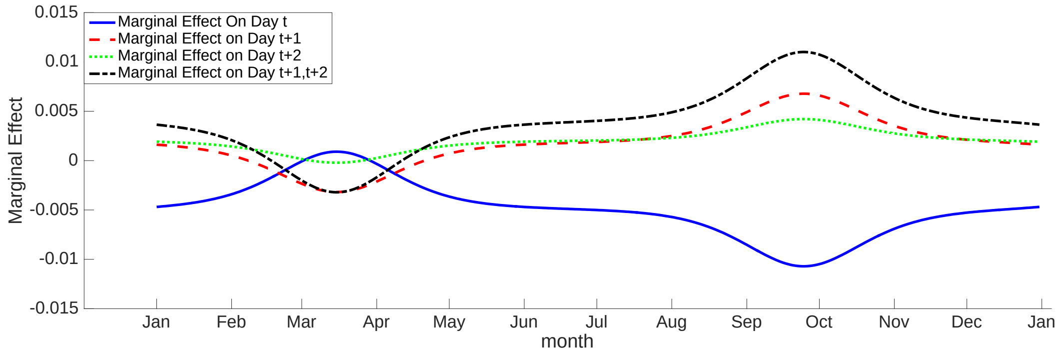

Figure 1 depicts the marginal effect of FEARS on S&P 500 returns by choosing the full range of Onset on day 0, day 1, day 2, and days 1 and 2. The solid blue line depicts the simple slope on day 0. The red dashed line depicts the simple slope on day1. The green dotted line depicts the simple slope on day 2. The black dotted-dashed line depicts the simple slope on days 1 and day 2.

Table 4 Sentiment, Seasonal Mispricing Correction Pattern, and Equity returns

Panel A: FEARS, Onset and CRSP EW				
	(1)	(2)	(3)	(4)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Fears$	-0.0048***	0.0017*	0.0019**	0.0035***
	(0.0015)	(0.0010)	(0.00085)	(0.0013)
$Fears \times Onset$	-0.0129	0.0138**	0.0053	0.0191*
	(0.0080)	(0.0066)	(0.0069)	(0.0109)
$Onset$	-0.0013	-0.0018	-0.0020	-0.0038
	(0.0016)	(0.0015)	(0.0015)	(0.0029)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0420	0.0169	0.0155	0.0180
Panel B: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0103***	0.0076**	0.0041	0.0117**
	(0.0040)	(0.0031)	(0.0033)	(0.0052)
$Onset_M$	-0.0048***	0.0017*	0.0018**	0.0035***
	(0.0015)	(0.0010)	(0.00085)	(0.0013)
$Onset_L$	0.00065	-0.0042	-0.0004	-0.0046
	(0.0015)	(0.0028)	(0.0028)	(0.0044)

Panel C: FEARS, Onset CRSP VW				
	(1)	(2)	(3)	(4)
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Fears$	-0.0049***	0.0019*	0.0020**	0.0039***
	(0.0016)	(0.0009)	(0.0010)	(0.0014)
$Fears \times Onset$	-0.0135	0.0127*	0.0053	0.0179*
	(0.0086)	(0.0067)	(0.0077)	(0.0108)
$Onset$	-6.6986e-04	-0.0013	-0.0014	-0.0027
	(0.0017)	(0.0016)	(0.0015)	(0.0029)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0586	0.0274	0.0182	0.0292
Panel D: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0106**	0.0073**	0.0043	0.0116**
	(0.0043)	(0.0032)	(0.0037)	(0.0053)
$Onset_M$	-0.0049***	0.0019*	0.0020**	0.0039***
	(0.0016)	(0.0009)	(0.0010)	(0.0014)
$Onset_L$	0.0009	-0.0035	-0.0003	-0.0037
	(0.0036)	(0.0029)	(0.0031)	(0.0044)

Table 4 (continued)

Panel E: FEARS, Onset and SPY				
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
$Fears$	-0.0048***	0.0019**	0.0016	0.0036***
	(0.0016)	(0.0009)	(0.0009)	(0.0014)
$Fears \times Onset$	-0.0165*	0.0133*	0.0043	0.0175
	(0.0100)	(0.0069)	(0.0075)	(0.0112)
$Onset$	-3.9925e-04	-0.0011	-0.0011	-0.0022
	(0.0017)	(0.0016)	(0.0015)	(0.0029)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0657	0.0339	0.0210	0.0359

Panel F: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0119**	0.0076**	0.0035	0.0111**
	(0.0050)	(0.0033)	(0.0036)	(0.0054)
$Onset_M$	-0.0048***	0.0019**	0.0016	0.0036**
	(0.0016)	(0.0009)	(0.0009)	(0.0014)
$Onset_L$	0.0022	-0.0038	0.0002	-0.0039
	(0.0040)	(0.0030)	(0.0031)	(0.0045)

Panel G: FEARS, Onset and QQQ				
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
$Fears$	-0.0042***	0.0019*	0.0017	0.0036**
	(0.0014)	(0.0011)	(0.0010)	(0.0015)
$Fears \times Onset$	-0.0094	0.0124	0.0039	0.0160
	(0.0077)	(0.0088)	(0.0078)	(0.0124)
$Onset$	1.7282e-04	-5.5338e-04	-6.8252e-04	-0.0012
	(0.0017)	(0.0016)	(0.0015)	(0.0030)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0345	0.0176	0.0109	0.0161

Panel H: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0082**	0.0072*	0.0033	0.0104*
	(0.0039)	(0.0042)	(0.0037)	(0.0060)
$Onset_M$	-0.0042***	0.0019*	0.0017	0.0036**
	(0.0014)	(0.0011)	(0.0010)	(0.0015)
$Onset_L$	-0.0001	-0.0034	0.0000	-0.0032
	(0.0033)	(0.0037)	(0.0033)	(0.0049)

Table 4 (continued)

Panel I: FEARS, Onset and IWB				
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
$Fears$	-0.0047***	0.0020**	0.0017	0.0037***
	(0.0015)	(0.0010)	(0.0010)	(0.0014)
$Fears \times Onset$	-0.0121	0.0115*	0.0049	0.0164
	(0.0084)	(0.0065)	(0.0077)	(0.0108)
$Onset$	-0.0005	-0.0012	-0.0012	-0.0024
	(0.0016)	(0.0016)	(0.015)	(0.0028)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0574	0.0274	0.0177	0.0288

Panel J: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0098**	0.0069**	0.0038	0.0107**
	(0.0043)	(0.0031)	(0.0037)	(0.0053)
$Onset_M$	-0.0047***	0.0020**	0.0017	0.0037***
	(0.0015)	(0.0010)	(0.0010)	(0.0014)
$Onset_L$	0.0005	-0.0030	-0.0004	-0.0033
	(0.0035)	(0.0028)	(0.0031)	(0.0044)

Panel K: FEARS, Onset and IWM				
	(1) Ret(t)	(2) Ret(t+1)	(3) Ret(t+2)	(4) Ret[t+1,t+2]
$Fears$	-0.0049**	0.0023*	0.0020	0.0043**
	(0.0020)	(0.0014)	(0.0013)	(0.0019)
$Fears \times Onset$	-0.0103	0.0198**	0.0026	0.0221*
	(0.0075)	(0.0085)	(0.0081)	(0.0115)
$Onset$	-7.8145e-04	-0.0016	-0.0017	-0.0033
	(0.021)	(0.0020)	(0.0018)	(0.0036)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0461	0.0256	0.0139	0.0254

Panel L: Test the significance of marginal effects: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret(t+1)	Ret(t+2)	Ret[t+1,t+2]
$Onset_H$	-0.0093**	0.0108***	0.0031	0.0138**
	(0.0039)	(0.0040)	(0.0038)	(0.0056)
$Onset_M$	-0.0049**	0.0023*	0.0020	0.0043**
	(0.0020)	(0.0014)	(0.0013)	(0.0019)
$Onset_L$	-0.0005	-0.0061*	0.0009	-0.0051
	(0.0036)	(0.0037)	(0.0036)	(0.0049)

Panels A-L show the estimates of the regression of the test assets over 0-2 days on the FEARS, Onset and the interaction of FEARS and Onset. Specifically, Ret[t+1,t+2] is cumulative returns from t+1 to t+2. The test assets include CRSP equally weighted and value-weighted portfolios, the SPDR S&P 500 (SPY), the PowerShare QQQ (QQQ), the iShares Russell 1000 (IWB) and the iShares Russell 2000 (IWM). Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Figure 2 Marginal Effect of FEARS on Equity Returns

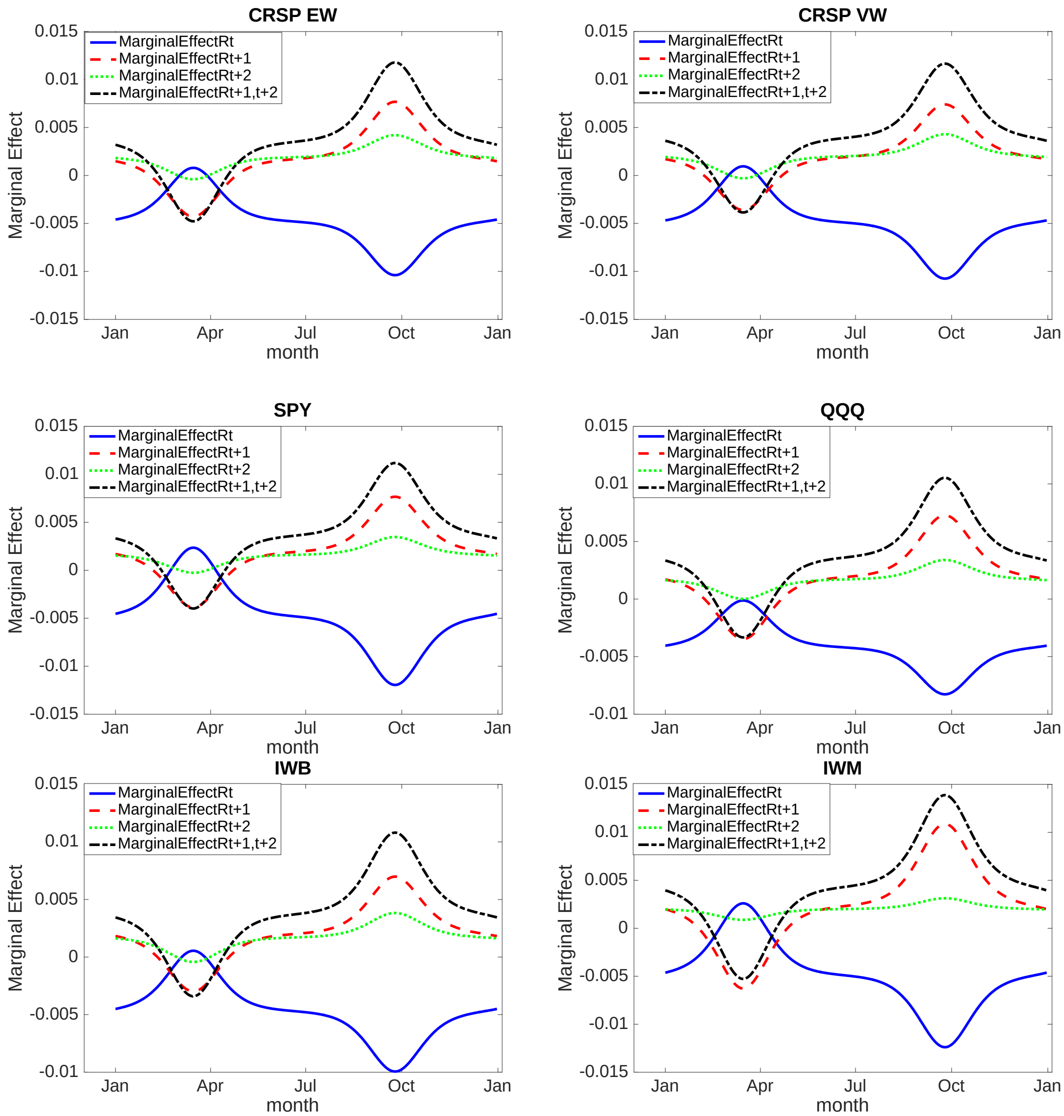

Figure 2 depicts the marginal effects by choosing the full range of Onset on day 0, day 1, day 2 and day 1 and 2. The solid blue line depicts the simple slope on day 0. The red dashed line depicts the simple slope on day1. The green dotted line depicts the simple slope on day 2. And the black dotted-dashed line depicts the simple slope on day 1 and day 2. CRSP EW represents CRSP equally weighted portfolios. CRSP VW represents CRSP value-weighted portfolios. SPY, QQQ, IWB, and IWM represents 4 highly liquid ETF index: the SPDR S&P 500, the PowerShare QQQ, the iShares Russell 1000, and iShares Russell 2000, respectively.

Table 5 FEARS, Seasonality, and Hard to Arbitrage portfolios

Panel A:	High Scholes-William Beta		High Total Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0080***	0.0069***	-0.0063***	0.0051***
	(0.0028)	(0.0025)	(0.0020)	(0.0019)
$Fears \times Onset$	-0.0154	0.0321*	-0.0151	0.0232*
	(0.0130)	(0.0184)	(0.0098)	(0.0134)
$Onset$	-0.0026	-0.0075	-0.0025	-0.0067
	(0.0030)	(0.0054)	(0.0022)	(0.0042)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1889	1891	1889
R^2	0.0308	0.0199	0.0537	0.0558
Panel B: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears\times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0145**	0.0206**	-0.0127***	0.0150**
	(0.0064)	(0.0088)	(0.0049)	(0.0065)
$Onset_M$	-0.0080***	0.0069***	-0.0063***	0.0051***
	(0.0028)	(0.0025)	(0.0020)	(0.0019)
$Onset_L$	-0.0014	-0.0068	0.0001	-0.0048
	(0.0060)	(0.0075)	(0.0044)	(0.0056)
Panel C:	High Downside Beta		High Downside Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0088***	0.0078***	-0.0067***	0.0048**
	(0.0031)	(0.0027)	(0.0022)	(0.0020)
$Fears \times Onset$	-0.0223	0.0354*	-0.0179*	0.0238*
	(0.0144)	(0.0194)	(0.0100)	(0.0139)
$Onset$	-0.0028	-0.0079	-0.0033	-0.0083**
	(0.0031)	(0.0055)	(0.0022)	(0.0042)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1889	1891	1889
R^2	0.0361	0.0226	0.0656	0.0690
Panel D: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears\times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0183**	0.0229**	-0.0143***	0.0150**
	(0.0073)	(0.0094)	(0.0051)	(0.0067)
$Onset_M$	-0.0088***	0.0078***	-0.0067***	0.0048**
	(0.0031)	(0.0027)	(0.0022)	(0.0020)
$Onset_L$	7.11e-04	-0.0074	9.49e-04	-0.0054
	(0.0065)	(0.0079)	(0.0045)	(0.0057)

This table links FEARS and Onset to daily hard-to-arbitrage portfolios constructed by sorting on stock characteristics. We create decile portfolios, and high is defined as the value in the top decile. Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; And lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears\times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 6 FEARS, Seasonality, and Easy to Arbitrage portfolios

Panel A:	Low Scholes-William Beta		Low Total Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0025***	0.0014***	-0.0027***	0.0010*
	(0.00058)	(0.0005)	(0.00078)	(0.00058)
$Fears \times Onset$	-0.0100*	0.0043	-0.0159*	0.0068
	(0.0057)	(0.0042)	(0.0094)	(0.0073)
$Onset$	-0.00088	-0.0023*	-0.0006	-0.0018
	(0.0006)	(0.0013)	(0.0006)	(0.0014)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1889	1891	1889
R^2	0.1054	0.0733	0.1171	0.0299
Panel B: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0068**	0.0032	-0.0094**	0.0039
	(0.0028)	(0.0021)	(0.0046)	(0.0036)
$Onset_M$	-0.0025***	0.0014***	-0.0027***	0.0010*
	(0.00058)	(0.0005)	(0.00078)	(0.00058)
$Onset_L$	0.0018	-0.00045	0.0041	-0.0019
	(0.0021)	(0.0016)	(0.0035)	(0.0027)

Panel C:	Low Downside Beta		Low Downside Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0013***	0.00016	-0.0018***	0.0005
	(0.00036)	(0.00047)	(0.0005)	(0.0004)
$Fears \times Onset$	-0.0045*	0.00066	-0.0111*	0.0033
	(0.0025)	(0.0027)	(0.0061)	(0.0052)
$Onset$	-0.0006	-0.0017*	-0.0006	-0.0017
	(0.00048)	(0.0010)	(0.00056)	(0.0012)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1889	1891	1889
R^2	0.0861	0.0905	0.0674	0.0247
Panel D: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0032***	0.00044	-0.0065**	0.0019
	(0.0012)	(0.0013)	(0.0030)	(0.0025)
$Onset_M$	-0.0013***	0.00016	-0.0018***	0.0005
	(0.00036)	(0.00047)	(0.0005)	(0.0004)
$Onset_L$	0.00066	-0.00012	0.0030	-0.0087
	(0.0010)	(0.0012)	(0.0023)	(0.0020)

This table links FEARS and Onset to daily easy-to-arbitrage portfolios constructed by sorting on stock characteristics. We create decile portfolios, and low is defined as the value in the bottom decile. Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; And lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 7 FEARS's Error and Equity returns

	(1) Ret(t)	(2) Ret[t+1,t+2]	(3) Ret(t)	(4) Ret[t+1,t+2]
	FEARS		SD(FEARS)	
SP500	-1.26e-04	0.0041***	0.0014	0.0015
CRSP VW	-1.06e-04	0.0042***	0.0014	0.0015
CRSP EW	-7.75e-04	0.0037***	0.0014	0.0014
SPY	-1.56e-04	0.0040**	0.0015	0.0015
QQQ	4.07e-04	0.0035**	0.0013	0.0016
IWB	2.23e-05	0.0039**	0.0014	0.0015
IWM	4.13e-04	0.0046**	0.0019	0.0020
	R^2		Other Controls	
SP500	0.0476	0.0331	Yes	Yes
CRSP VW	0.0400	0.0248	Yes	Yes
CRSP EW	0.0209	0.0118	Yes	Yes
SPY	0.0453	0.0322	Yes	Yes
QQQ	0.0227	0.0128	Yes	Yes
IWB	0.0400	0.0249	Yes	Yes
IWM	0.0354	0.0211	Yes	Yes

This table shows the estimates of the regression of the test assets over 0-2 days on the orthogonalized FEARS. Specifically, Ret[t+1,t+2] is cumulative returns from t+1 to t+2. The test assets include SP500 index, CRSP equally weighted and value-weighted portfolios, the SPDR S&P 500 (SPY), the PowerShare QQQ (QQQ), the iShares Russell 1000 (IWB) and the iShares Russell 2000 (IWM). The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 8 FEARS's Error and Industrial returns

	(1) Ret(t)	(2) Ret[t+1,t+2]	(3) Ret(t)	(4) Ret[t+1,t+2]
	FEARS		SD(FEARS)	
Industry (1)	6.52e-05	0.0030**	0.0011	0.0013
Industry (2)	-1.89e-04	0.0048***	0.0015	0.0016
Industry (3)	-1.86e-04	0.0041***	0.0014	0.0015
Industry (4)	-2.62e-04	0.0032**	0.0011	0.0013
Industry (5)	1.11e-05	0.0048**	0.0019	0.0021
	R^2		Other Controls	
Industry (1)	0.0347	0.0269	Yes	Yes
Industry (2)	0.0450	0.0317	Yes	Yes
Industry (3)	0.0296	0.0198	Yes	Yes
Industry (4)	0.0362	0.0266	Yes	Yes
Industry (5)	0.0366	0.0246	Yes	Yes

This table shows the estimates of the regression of the test assets over 0-2 days on the orthogonalized FEARS. Specifically, Ret[t+1,t+2] is cumulative returns from t+1 to t+2. Industry (1) are portfolios from Consumer Durables, Nondurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops); Industry (2) are portfolios from Manufacturing, Energy, and Utilities; Industry (3) are portfolios from Business Equipment, Telephone and Television Transmission; Industry (4) are portfolios from Healthcare, Medical Equipment, and Drugs; Industry (5) are portfolios from others such as Mines, Entertainment, and Finance. In each regression, the main independent variable is the FEARS index. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 9 FEARS's Error and Limits to Arbitrage

High-Low	(1) Ret(t)	(2) Ret[t+1,t+2]	(3) Ret(t)	(4) Ret[t+1,t+2]
	FEARS		SD(FEARS)	
Beta	0.0016	0.0055**	0.0023	0.0024
Volatility	5.65e-04	0.0040**	0.0016	0.0017
Downside Beta	-1.26e-04	0.0071**	0.0027	0.0028
Downside Volatility	-0.0011	0.0043**	0.0019	0.0018
	R^2		Other Controls	
Beta	0.0190	0.0141	Yes	Yes
Volatility	0.0425	0.0621	Yes	Yes
Downside Beta	0.0246	0.0230	Yes	Yes
Downside Volatility	0.0559	0.0799	Yes	Yes

This table links FEARS to daily high-minus-low return spreads on portfolios constructed by sorting on stock characteristics. We create decile portfolios, where high is defined as the value in the top decile and low is defined as the value in the bottom decile. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 10 FEARS's Error, Seasonality and Equity Returns

	(1) Ret(t)	(2) Ret[t+1,t+2]	(3) Ret(t)	(4) Ret[t+1,t+2]
	$FEARS$		$SD(FEARS)$	
SP500	2.19e-05	0.0039***	0.0014	0.0014
CRSP VW	4.45e-05	0.0039***	0.0014	0.0014
CRSP EW	-5.98e-04	0.0033**	0.0014	0.0013
SPY	5.46e-05	0.0037***	0.0014	0.0014
QQQ	4.93e-04	0.0033**	0.0013	0.0015
IWB	1.55e-04	0.0036**	0.0014	0.0014
IWM	5.16e-04	0.0042**	0.0019	0.0019
	$FEARS \times Onset$		$SD(FEARS \times Onset)$	
SP500	-0.0071	0.0122	0.0071	0.0093
CRSP VW	-0.0073	0.0135	0.0070	0.0096
CRSP EW	-0.0086	0.0150	0.0066	0.0094
SPY	-0.0101	0.0136	0.0079	0.0098
QQQ	-0.0040	0.0105	0.0066	0.0105
IWB	-0.0064	0.0121	0.0070	0.0095
IWM	-0.0050	0.0168*	0.0073	0.0099
	$Onset$		SD($Onset$)	
SP500	-3.27e-04	-0.0022	0.0017	0.0029
CRSP VW	-6.16e-04	-0.0027	0.0017	0.0029
CRSP EW	-0.0012	-0.0038	0.0016	0.0029
SPY	-3.45e-04	-0.0022	0.0017	0.0029
QQQ	2.33e-04	-0.0012	0.0017	0.0030
IWB	-4.58e-04	-0.0024	0.0016	0.0028
IWM	-7.18e-04	-0.0033	0.0021	0.0036
	$R2$		Other Controls	
SP500	0.0485	0.0357	Yes	Yes
CRSP VW	0.0410	0.0278	Yes	Yes
CRSP EW	0.0228	0.0159	Yes	Yes
SPY	0.0471	0.0352	Yes	Yes
QQQ	0.0230	0.0144	Yes	Yes
IWB	0.0408	0.0277	Yes	Yes
IWM	0.0357	0.0237	Yes	Yes

This table shows the estimates of the regression of the test assets over 0-2 days on the orthogonalized FEARS, Onset and the interaction of orthogonalized FEARS and Onset. Specifically, Ret[t+1,t+2] is cumulative returns from t+1 to t+2. The test assets include SPt00 index, CRSP equally weighted and value-weighted portfolios, the SPDR S&P 500 (SPY), the PowerShare QQQ (QQQ), the iShares Russell 1000 (IWB) and the iShares Russell 2000 (IWM). Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 11 FEARS's Error, Seasonality and Industrial Portfolios

	(1) Ret(t)	(2) Ret[t+1,t+2]	(3) Ret(t)	(4) Ret[t+1,t+2]
	$FEARS$		$SD(FEARS)$	
Industry (1)	1.06e-04	0.0028**	0.0011	0.0012
Industry (2)	4.51e-05	0.0044***	0.0015	0.0014
Industry (3)	-5.48e-05	0.0038***	0.0014	0.0014
Industry (4)	-9.16e-05	0.0030**	0.0010	0.0012
Industry (5)	1.23e-04	0.0046**	0.0019	0.0020
	$FEARS \times Onset$		$SD(FEARS \times Onset)$	
Industry (1)	-0.0021	0.0082	0.0051	0.0080
Industry (2)	-0.0113	0.0194*	0.0085	0.0104
Industry (3)	-0.0061	0.0122	0.0071	0.0101
Industry (4)	-0.0082	0.0097	0.0061	0.0074
Industry (5)	-0.0055	0.0124	0.0091	0.0108
	$Onset$		$SD(Onset)$	
Industry (1)	-7.20e-04	-0.0026	0.0014	0.0024
Industry (2)	-9.37e-04	-0.0032	0.0018	0.0031
Industry (3)	-4.73e-05	-0.0017	0.0016	0.0028
Industry (4)	-7.75e-05	-0.0014	0.0013	0.0023
Industry (5)	-5.41e-04	-0.0030	0.0024	0.0040
	$R2$		$Other\ Contorls$	
Industry (1)	0.0349	0.0290	Yes	Yes
Industry (2)	0.0468	0.0356	Yes	Yes
Industry (3)	0.0302	0.0214	Yes	Yes
Industry (4)	0.0381	0.0283	Yes	Yes
Industry (5)	0.0369	0.0260	Yes	Yes

This table shows the estimates of the regression of the test assets over 0-2 days on the orthogonalized FEARS, Onset and the interaction of orthogonalized FEARS and Onset. Specifically, Ret[t+1,t+2] is cumulative returns from t+1 to t+2. Industry (1) are portfolios from Consumer Durables, Nondurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops); Industry (2) are portfolios from Manufacturing, Energy, and Utilities; Industry (3) are portfolios from Business Equipment, Telephone and Television Transmission; Industry (4) are portfolios from Healthcare, Medical Equipment, and Drugs; Industry (5) are portfolios from others such as Mines, Entertainment, and Finance. Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; and lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 12 FEARS's Error, Seasonality, and Hard to Arbitrage

Panel A:	High Scholes-William Beta		High Total Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	0.0002	0.0063***	-0.0009	0.0049***
	(0.0025)	(0.0025)	(0.0018)	(0.0019)
$Fears \times Onset$	-0.0115	0.0248	-0.0132	0.0196*
	(0.0116)	(0.0157)	(0.0085)	(0.0119)
$Onset$	-0.0025	-0.0075	-0.0024	-0.0067
	(0.0030)	(0.0054)	(0.0023)	(0.0043)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0177	0.0177	0.0390	0.0545
Panel B: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears\times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0047	0.0169**	-0.0066	0.0132**
	(0.0054)	(0.0076)	(0.0041)	(0.0058)
$Onset_M$	0.0002	0.0063***	-0.0009	0.0049***
	(0.0025)	(0.0025)	(0.0018)	(0.0019)
$Onset_L$	0.0051	-0.0042	0.0047	-0.0035
	(0.0057)	(0.0066)	(0.0041)	(0.0050)
Panel C:	High Downside Beta		High Downside Volatility	
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0002	0.0073***	-0.0015	0.0045**
	(0.0028)	(0.0027)	(0.0020)	(0.0019)
$Fears \times Onset$	-0.0159	0.0278*	-0.0139	0.0190
	(0.0129)	(0.0166)	(0.0087)	(0.0125)
$Onset$	-0.0027	-0.0079	-0.0033	-0.0083
	(0.0031)	(0.0055)	(0.0022)	(0.0042)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0208	0.0204	0.0492	0.0675
Panel D: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears\times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0070	0.0192**	-0.0075*	0.0126**
	(0.0060)	(0.0082)	(0.0043)	(0.0061)
$Onset_M$	-0.0002	0.0073***	-0.0015	0.0045**
	(0.0028)	(0.0027)	(0.0020)	(0.0019)
$Onset_L$	0.0066	-0.0046	0.0044	-0.0036
	(0.0063)	(0.0069)	(0.0041)	(0.0052)

This table links orthogonalized FEARS and Onset to daily hard-to-arbitrage portfolios constructed by sorting on stock characteristics. We create decile portfolios, and high is defined as the value in the top decile. Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; And lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears\times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Appendix A

Correction speed test

The test statistic is given by

$$g(\theta) = \frac{\beta_{t+k}^{H}}{-\beta^{H}} - \frac{\beta_{t+k}^{M}}{-\beta^{M}} = \frac{\beta_{t+k}^{M}\beta^{H} - \beta^{M}\beta_{t+k}^{H}}{\beta^{M}\beta^{H}}$$

where the β^{H} and β_{t+k}^{H} represent the marginal effects from model (1) when $Onset$ takes the high value, and β^{M} and β_{t+k}^{M} are the marginal effects when $Onset$ takes the medium value.

We are testing whether $g(\theta) > 0$. Thus, we redefine function g as follows:

$$g(\theta) = (\beta_{t+k}^{M}\beta^{H} - \beta^{M}\beta_{t+k}^{H})\, \beta^{M}\beta^{H}$$

To test the hypothesis is then a one-side test as in

$$H_0: g(\theta) > 0$$
$$H_1: g(\theta) \leq 0$$

Let θ_T be an estimate of θ. We have the following result:

$$g(\theta_T) - g(\theta) \xrightarrow{d} N(0, \frac{1}{T}\frac{\partial g}{\partial \theta'}\Sigma\frac{\partial g}{\partial \theta})$$

Where Σ is from GMM approach.

If $\Pr\left(\mathrm{t}_{\mathrm{T}-1} < \frac{\mathrm{g}(\theta_{\mathrm{T}})}{\sigma_{\mathrm{g}}}\right) < 0.95$, then we reject the null hypothesis.

Appendix B

Table B1 P Values of Marginal Effects on Contemporaneous S&P 500 returns

Julian	P value	Julian	P value	Julian	P value
1	0.002140971	51	0.558741369	101	0.50215375
2	0.002206274	52	0.60609947	102	0.454953977
3	0.00227758	53	0.652954635	103	0.408863398
4	0.002355716	54	0.698879608	104	0.364407393
5	0.002441645	55	0.743501558	105	0.322075573
6	0.002536486	56	0.786506479	106	0.282297506
7	0.002641554	57	0.827639865	107	0.245421491
8	0.002758393	58	0.866704281	108	0.211698699
9	0.002888822	59	0.90355483	109	0.181274543
10	0.003034997	60	0.938093152	110	0.154188113
11	0.003199483	61	0.970260763	111	0.130379478
12	0.003385337	62	0.999967818	112	0.10970356
13	0.003596229	63	0.972591714	113	0.091948496
14	0.00383657	64	0.947589861	114	0.076856116
15	0.004111693	65	0.92492652	115	0.064142131
16	0.004428064	66	0.904556119	116	0.053514216
17	0.004793556	67	0.886427356	117	0.044686704
18	0.005217788	68	0.870486639	118	0.03739139
19	0.005712554	69	0.856680899	119	0.031384489
20	0.006292353	70	0.844959868	120	0.026450227
21	0.006975062	71	0.835277873	121	0.022401768
22	0.007782766	72	0.827595245	122	0.019080219
23	0.008742786	73	0.82187938	123	0.016352421
24	0.009888944	74	0.81810554	124	0.014108091
25	0.011263102	75	0.816257398	125	0.012256732
26	0.012916997	76	0.816327406	126	0.010724601
27	0.014914413	77	0.81831696	127	0.009451917
28	0.017333651	78	0.82223643	128	0.00839038
29	0.020270283	79	0.828104983	129	0.007501047
30	0.023840049	80	0.835950258	130	0.00675254
31	0.028181719	81	0.845807814	131	0.006119571
32	0.033459575	82	0.857720348	132	0.005581737
33	0.039865108	83	0.871736608	133	0.005122544
34	0.047617321	84	0.887909978	134	0.004728625
35	0.056960995	85	0.906296621	135	0.004389119
36	0.068162222	86	0.926953134	136	0.004095165
37	0.081500623	87	0.949933618	137	0.003839514
38	0.097257912	88	0.975286111	138	0.00361621
39	0.115702952	89	0.996951732	139	0.003420341
40	0.137073945	90	0.966757685	140	0.003247838
41	0.16155911	91	0.934130788	141	0.003095317
42	0.189277729	92	0.899097825	142	0.002959955
43	0.220263752	93	0.86172034	143	0.00283938
44	0.254454125	94	0.822101859	144	0.0027316
45	0.291683625	95	0.780394925	145	0.002634927
46	0.331687152	96	0.736807304	146	0.00254793
47	0.374109444	97	0.691606676	147	0.00246939
48	0.418521232	98	0.645122921	148	0.002398263
49	0.464440017	99	0.597747099	149	0.002333652
50	0.511353206	100	0.549926303	150	0.002274787

Table B1 (continued)

Julian	P value	Julian	P value	Julian	P value
151	0.002220999	201	0.001270466	251	0.009804857
152	0.002171709	202	0.001260689	252	0.010346372
153	0.002126411	203	0.001251662	253	0.0108848
154	0.002084664	204	0.001243499	254	0.011415959
155	0.002046083	205	0.001236326	255	0.011935604
156	0.002010326	206	0.001230286	256	0.01243949
157	0.001977093	207	0.001225531	257	0.012923426
158	0.00194612	208	0.001222231	258	0.013383337
159	0.00191717	209	0.001220573	259	0.013815312
160	0.001890034	210	0.00122076	260	0.014215651
161	0.001864524	211	0.001223017	261	0.014580913
162	0.001840473	212	0.00122759	262	0.014907949
163	0.001817731	213	0.001234751	263	0.01519394
164	0.001796162	214	0.001244797	264	0.015436422
165	0.001775644	215	0.001258057	265	0.01563331
166	0.001756067	216	0.001274893	266	0.015782918
167	0.001737331	217	0.001295706	267	0.01588397
168	0.001719345	218	0.001320935	268	0.015935618
169	0.001702027	219	0.00135107	269	0.01593744
170	0.001685302	220	0.00138665	270	0.015889447
171	0.001669101	221	0.00142827	271	0.015792085
172	0.001653362	222	0.001476587	272	0.015646225
173	0.001638027	223	0.001532322	273	0.015453159
174	0.001623045	224	0.001596268	274	0.015214588
175	0.001608368	225	0.00166929	275	0.014932604
176	0.001593953	226	0.00175233	276	0.014609674
177	0.001579761	227	0.001846405	277	0.014248612
178	0.001565757	228	0.001952606	278	0.013852554
179	0.001551908	229	0.002072092	279	0.013424919
180	0.001538187	230	0.002206085	280	0.012969379
181	0.001524569	231	0.002355851	281	0.012489808
182	0.001511033	232	0.00252269	282	0.01199024
183	0.001497562	233	0.002707911	283	0.011474813
184	0.001484141	234	0.002912801	284	0.01094772
185	0.001470759	235	0.003138601	285	0.010413147
186	0.001457411	236	0.003386463	286	0.00987522
187	0.001444092	237	0.003657409	287	0.009337939
188	0.001430804	238	0.003952294	288	0.00880513
189	0.001417553	239	0.004271756	289	0.008280386
190	0.001404349	240	0.004616171	290	0.00776702
191	0.001391205	241	0.004985617	291	0.007268025
192	0.001378142	242	0.00537983	292	0.006786035
193	0.001365185	243	0.005798176	293	0.006323303
194	0.001352366	244	0.006239624	294	0.005881683
195	0.00133972	245	0.006702734	295	0.005462627
196	0.001327292	246	0.007185649	296	0.005067187
197	0.001315132	247	0.007686104	297	0.004696029
198	0.0013033	248	0.008201439	298	0.004349458
199	0.00129186	249	0.008728629	299	0.004027446
200	0.001280887	250	0.009264316	300	0.003729667

Table B1 (continued)

Julian	P value	Julian	P value	Julian	P value
301	0.00345554	323	0.001248616	345	0.001425012
302	0.003204269	324	0.001237351	346	0.00144521
303	0.002974885	325	0.001229181	347	0.001466185
304	0.002766291	326	0.001223817	348	0.001487969
305	0.002577298	327	0.001220999	349	0.001510605
306	0.00240666	328	0.001220492	350	0.001534146
307	0.002253111	329	0.001222083	351	0.001558658
308	0.002115384	330	0.001225581	352	0.00158422
309	0.001992242	331	0.001230814	353	0.001610924
310	0.001882485	332	0.001237627	354	0.001638878
311	0.001784975	333	0.001245882	355	0.001668206
312	0.001698633	334	0.001255455	356	0.001699051
313	0.001622454	335	0.001266237	357	0.001731575
314	0.001555505	336	0.001278131	358	0.001765965
315	0.001496927	337	0.001291052	359	0.001802431
316	0.001445931	338	0.001304929	360	0.001841215
317	0.0014018	339	0.0013197	361	0.00188259
318	0.00136388	340	0.001335315	362	0.001926868
319	0.00133158	341	0.001351734	363	0.001974408
320	0.001304364	342	0.001368928	364	0.002025615
321	0.001281748	343	0.001386877	365	0.002080957
322	0.001263297	344	0.001405572	366	0.002140971

This table shows the p value of the simple slope of contemporaneous S&P 500 returns within the full range of $Onset$. The Julian refers to the day of the year. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$, where the variances are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator.

Table B2 P values of Marginal Effects on S&P 500 Returns of Day 1

Julian	P value	Julian	P value	Julian	P value
1	0.08381904	51	0.522091901	101	0.556949815
2	0.087177041	52	0.495407794	102	0.589027264
3	0.090789615	53	0.470875382	103	0.623597134
4	0.094686355	54	0.448377406	104	0.660698916
5	0.098900451	55	0.427791803	105	0.700333342
6	0.103469127	56	0.408995414	106	0.74245462
7	0.108434145	57	0.391866855	107	0.786963359
8	0.113842354	58	0.376288712	108	0.833700962
9	0.119746287	59	0.362149092	109	0.882446259
10	0.12620479	60	0.349342703	110	0.932915171
11	0.133283711	61	0.337771504	111	0.984763956
12	0.141056577	62	0.327345047	112	0.962403587
13	0.149605276	63	0.317980588	113	0.909024995
14	0.159020727	64	0.309603016	114	0.855564694
15	0.169403422	65	0.302144664	115	0.802496977
16	0.180863846	66	0.295545042	116	0.750287889
17	0.193522673	67	0.289750533	117	0.699377334
18	0.207510632	68	0.284714061	118	0.650162992
19	0.222967897	69	0.280394765	119	0.602987227
20	0.24004295	70	0.276757688	120	0.558127958
21	0.258890624	71	0.27377349	121	0.515793831
22	0.279669332	72	0.271418198	122	0.476123667
23	0.302537171	73	0.269672986	123	0.439189691
24	0.327646939	74	0.268524009	124	0.405003774
25	0.355139934	75	0.267962269	125	0.373525704
26	0.385138612	76	0.267983537	126	0.344672605
27	0.417738314	77	0.268588309	127	0.318328609
28	0.452998379	78	0.269781827	128	0.294354139
29	0.490933201	79	0.271574129	129	0.272594247
30	0.531503933	80	0.273980155	130	0.252885882
31	0.574611609	81	0.277019904	131	0.235063728
32	0.620092573	82	0.280718625	132	0.218964868
33	0.667717015	83	0.285107059	133	0.204432177
34	0.717191182	84	0.29022172	134	0.191316711
35	0.768163577	85	0.296105208	135	0.179479221
36	0.820235008	86	0.302806549	136	0.16879097
37	0.872971977	87	0.310381555	137	0.15913399
38	0.925922349	88	0.318893179	138	0.150400984
39	0.978632289	89	0.328411857	139	0.142494926
40	0.969337125	90	0.339015799	140	0.135328485
41	0.918394766	91	0.350791191	141	0.128823348
42	0.868906835	92	0.363832281	142	0.122909479
43	0.821187582	93	0.378241263	143	0.117524383
44	0.775493647	94	0.394127912	144	0.112612367
45	0.732021929	95	0.411608865	145	0.108123861
46	0.690910666	96	0.430806464	146	0.104014745
47	0.65224312	97	0.451847048	147	0.100245776
48	0.616053151	98	0.474858569	148	0.096782022
49	0.582331998	99	0.49996743	149	0.093592387
50	0.551035599	100	0.527294436	150	0.090649155

Table B2 (continued)

Julian	P value	Julian	P value	Julian	P value
151	0.087927615	201	0.030646623	251	0.020375291
152	0.085405689	202	0.029676759	252	0.020840345
153	0.083063641	203	0.028711836	253	0.021294218
154	0.080883797	204	0.027754305	254	0.021734043
155	0.078850301	205	0.026806764	255	0.022157095
156	0.076948915	206	0.025871931	256	0.022560803
157	0.075166813	207	0.02495262	257	0.022942768
158	0.073492435	208	0.024051703	258	0.023300765
159	0.071915335	209	0.02317208	259	0.023632754
160	0.070426056	210	0.022316641	260	0.023936883
161	0.069016014	211	0.021488229	261	0.024211489
162	0.067677406	212	0.020689605	262	0.024455101
163	0.066403126	213	0.019923408	263	0.024666438
164	0.065186678	214	0.019192124	264	0.024844412
165	0.064022123	215	0.018498055	265	0.024988118
166	0.062904008	216	0.017843293	266	0.025096841
167	0.061827326	217	0.0172297	267	0.025170051
168	0.060787463	218	0.016658895	268	0.025207397
169	0.059780157	219	0.016132243	269	0.025208714
170	0.058801474	220	0.015650855	270	0.025174013
171	0.057847761	221	0.01521559	271	0.025103491
172	0.056915634	222	0.014827064	272	0.02499752
173	0.056001948	223	0.014485665	273	0.024856656
174	0.055103776	224	0.014191565	274	0.024681636
175	0.054218397	225	0.013944737	275	0.024473382
176	0.053343276	226	0.013744973	276	0.024232998
177	0.052476054	227	0.013591902	277	0.023961775
178	0.051614541	228	0.013484996	278	0.023661188
179	0.050756703	229	0.013423587	279	0.023332899
180	0.049900661	230	0.01340687	280	0.022978754
181	0.049044682	231	0.013433908	281	0.022600778
182	0.04818718	232	0.013503627	282	0.022201173
183	0.047326716	233	0.013614815	283	0.02178231
184	0.046461993	234	0.013766112	284	0.021346722
185	0.045591864	235	0.013956006	285	0.020897087
186	0.044715332	236	0.014182823	286	0.020436221
187	0.043831555	237	0.014444715	287	0.019967053
188	0.04293985	238	0.014739663	288	0.019492612
189	0.0420397	239	0.015065465	289	0.019016001
190	0.041130761	240	0.015419744	290	0.018540374
191	0.040212868	241	0.015799951	291	0.01806891
192	0.039286043	242	0.016203374	292	0.017604787
193	0.038350502	243	0.016627151	293	0.017151154
194	0.03740666	244	0.017068293	294	0.016711102
195	0.036455142	245	0.017523703	295	0.016287643
196	0.03549678	246	0.017990197	296	0.015883682
197	0.034532624	247	0.01846454	297	0.015502002
198	0.033563942	248	0.018943468	298	0.015145241
199	0.032592216	249	0.019423715	299	0.014815881
200	0.031619142	250	0.019902049	300	0.01451624

Table B2 (continued)

Julian	P value	Julian	P value	Julian	P value
301	0.01424847	323	0.018969087	345	0.042547783
302	0.014014551	324	0.019707834	346	0.043906102
303	0.013816298	325	0.020488443	347	0.045292501
304	0.01365537	326	0.021309429	348	0.046709475
305	0.013533274	327	0.022169188	349	0.04815996
306	0.01345138	328	0.023066023	350	0.049647368
307	0.013410927	329	0.023998177	351	0.05117561
308	0.013413037	330	0.024963866	352	0.052749136
309	0.013458722	331	0.025961307	353	0.054372976
310	0.013548886	332	0.026988758	354	0.056052787
311	0.013684333	333	0.02804455	355	0.057794908
312	0.013865764	334	0.029127121	356	0.059606428
313	0.014093769	335	0.030235044	357	0.061495252
314	0.014368826	336	0.031367062	358	0.063470192
315	0.014691285	337	0.032522114	359	0.065541069
316	0.015061362	338	0.03369936	360	0.06771881
317	0.015479122	339	0.034898205	361	0.070015599
318	0.015944467	340	0.036118323	362	0.072445001
319	0.016457127	341	0.037359676	363	0.075022148
320	0.01701665	342	0.038622532	364	0.077763927
321	0.017622399	343	0.039907484	365	0.080689198
322	0.018273548	344	0.041215468	366	0.08381904

This table shows the p value of the simple slope of S&P 500 returns on day 1 within the full range of $Onset$. The Julian refers to the day of the year. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$, where the variances are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator.

Table B3 P Values of Marginal Effects on 2-day Cumulative S&P 500 returns

Julian	P value	Julian	P value	Julian	P value
1	0.008850537	51	0.874518312	101	0.928554408
2	0.009176086	52	0.832481736	102	0.977355081
3	0.00953466	53	0.79334812	103	0.971097014
4	0.009931097	54	0.757070392	104	0.917036246
5	0.010371072	55	0.723566354	105	0.860793827
6	0.010861268	56	0.692728643	106	0.802802227
7	0.011409581	57	0.664433199	107	0.743593227
8	0.012025369	58	0.638546288	108	0.683788012
9	0.012719766	59	0.614930083	109	0.624078375
10	0.013506062	60	0.593447018	110	0.565199131
11	0.014400168	61	0.573963036	111	0.507893258
12	0.015421201	62	0.556349942	112	0.452872615
13	0.016592186	63	0.540487041	113	0.400778237
14	0.017940936	64	0.526262191	114	0.352144928
15	0.019501117	65	0.513572428	115	0.30737426
16	0.021313548	66	0.502324263	116	0.266719363
17	0.023427781	67	0.492433752	117	0.230282711
18	0.025903987	68	0.48382641	118	0.198026353
19	0.028815192	69	0.476437017	119	0.169792091
20	0.032249879	70	0.470209375	120	0.145328082
21	0.036314942	71	0.465096043	121	0.124317894
22	0.041138945	72	0.461058075	122	0.106408546
23	0.046875523	73	0.458064786	123	0.091234947
24	0.053706736	74	0.456093547	124	0.078439262
25	0.061845944	75	0.455129634	125	0.067684747
26	0.071539707	76	0.45516613	126	0.058664446
27	0.083067952	77	0.456203876	127	0.051105546
28	0.096741563	78	0.458251496	128	0.04477043
29	0.112896412	79	0.461325467	129	0.039455429
30	0.131883002	80	0.465450259	130	0.034988183
31	0.154051086	81	0.47065852	131	0.031224233
32	0.179729271	82	0.476991314	132	0.028043405
33	0.209200408	83	0.484498396	133	0.02534625
34	0.242674532	84	0.493238507	134	0.023050766
35	0.280262125	85	0.503279683	135	0.021089483
36	0.321951085	86	0.514699526	136	0.019406941
37	0.36759099	87	0.527585431	137	0.017957541
38	0.41688748	88	0.542034696	138	0.016703764
39	0.469408657	89	0.558154468	139	0.015614685
40	0.524603225	90	0.576061448	140	0.014664764
41	0.581828649	91	0.595881223	141	0.01383285
42	0.640386085	92	0.617747158	142	0.013101377
43	0.699557881	93	0.641798649	143	0.012455711
44	0.758643571	94	0.668178599	144	0.011883619
45	0.816991001	95	0.697029904	145	0.011374838
46	0.87402022	96	0.728490772	146	0.010920729
47	0.929239126	97	0.762688668	147	0.010513992
48	0.982251035	98	0.799732725	148	0.010148436
49	0.967244853	99	0.839704547	149	0.009818791
50	0.919458567	100	0.882647455	150	0.009520558

Table B3 (continued)

Julian	P value	Julian	P value	Julian	P value
151	0.009249875	201	0.004906936	251	0.0243832
152	0.009003424	202	0.004872236	252	0.025242466
153	0.008778338	203	0.004841259	253	0.026077273
154	0.008572133	204	0.004814478	254	0.02688307
155	0.008382649	205	0.004792408	255	0.027655503
156	0.008208006	206	0.004775608	256	0.028390447
157	0.008046553	207	0.00476468	257	0.02908403
158	0.007896846	208	0.004760276	258	0.029732653
159	0.007757612	209	0.004763097	259	0.030333003
160	0.007627726	210	0.0047739	260	0.030882066
161	0.007506193	211	0.004793494	261	0.03137713
162	0.007392128	212	0.004822752	262	0.031815792
163	0.007284743	213	0.004862608	263	0.032195958
164	0.007183336	214	0.004914062	264	0.032515841
165	0.007087277	215	0.004978185	265	0.032773965
166	0.006996001	216	0.005056119	266	0.032969154
167	0.006909001	217	0.005149083	267	0.033100539
168	0.00682582	218	0.005258371	268	0.033167548
169	0.006746045	219	0.005385353	269	0.033169909
170	0.006669304	220	0.005531475	270	0.033107649
171	0.006595259	221	0.005698251	271	0.032981089
172	0.006523605	222	0.00588726	272	0.032790847
173	0.006454067	223	0.006100134	273	0.03253784
174	0.006386396	224	0.006338545	274	0.032223283
175	0.006320366	225	0.006604181	275	0.031848691
176	0.006255776	226	0.006898732	276	0.03141588
177	0.006192443	227	0.007223852	277	0.030926968
178	0.006130207	228	0.007581134	278	0.030384372
179	0.006068924	229	0.007972065	279	0.02979081
180	0.006008472	230	0.008397991	280	0.029149291
181	0.005948743	231	0.008860069	281	0.028463112
182	0.005889647	232	0.009359223	282	0.027735846
183	0.005831115	233	0.009896095	283	0.026971324
184	0.00577309	234	0.010471005	284	0.026173621
185	0.005715537	235	0.011083906	285	0.025347027
186	0.005658437	236	0.011734349	286	0.02449602
187	0.005601788	237	0.012421455	287	0.023625231
188	0.005545611	238	0.013143894	288	0.022739404
189	0.005489944	239	0.013899877	289	0.02184335
190	0.005434845	240	0.014687151	290	0.020941902
191	0.005380395	241	0.015503012	291	0.020039859
192	0.005326698	242	0.016344326	292	0.019141932
193	0.00527388	243	0.01720756	293	0.018252689
194	0.005222093	244	0.018088819	294	0.017376502
195	0.005171513	245	0.018983896	295	0.016517488
196	0.005122347	246	0.019888321	296	0.015679464
197	0.005074826	247	0.020797422	297	0.014865904
198	0.005029213	248	0.021706378	298	0.014079896
199	0.004985804	249	0.02261028	299	0.013324117
200	0.004944925	250	0.023504192	300	0.012600814

Table B3 (continued)

Julian	P value	Julian	P value	Julian	P value
301	0.01191179	323	0.004932866	345	0.005521234
302	0.011258405	324	0.004876276	346	0.00560653
303	0.010641586	325	0.004831995	347	0.005695935
304	0.010061847	326	0.004799085	348	0.005789614
305	0.00951931	327	0.004776679	349	0.005887784
306	0.009013744	328	0.004763975	350	0.005990722
307	0.0085446	329	0.004760234	351	0.006098764
308	0.008111054	330	0.004764776	352	0.006212313
309	0.007712048	331	0.00477698	353	0.006331845
310	0.007346337	332	0.004796276	354	0.006457918
311	0.00701253	333	0.004822148	355	0.006591177
312	0.00670913	334	0.004854129	356	0.006732367
313	0.006434569	335	0.004891801	357	0.006882347
314	0.006187244	336	0.00493479	358	0.007042103
315	0.005965543	337	0.004982769	359	0.007212767
316	0.005767867	338	0.005035454	360	0.007395636
317	0.005592653	339	0.005092605	361	0.007592203
318	0.005438386	340	0.005154024	362	0.007804181
319	0.005303614	341	0.005219556	363	0.008033542
320	0.00518695	342	0.00528909	364	0.008282565
321	0.005087082	343	0.005362557	365	0.008553879
322	0.005002774	344	0.005439931	366	0.008850537

This table shows the p value of the simple slope of S&P 500 returns on 2-day cumulative S&P 500 returns within the full range of $Onset$. The Julian refers to the day of the year. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$, where the variances are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator.

Table B4 FEARS, Seasonality, and Limits to Arbitrage

Panel A:	Scholes-William Beta		Total Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0057**	0.0056**	-0.0036**	0.0040**
	(0.0024)	(0.0023)	(0.0017)	(0.0016)
$Fears \times Onset$	-0.0061	0.0292*	0.0027	0.0146*
	(0.0103)	(0.0156)	(0.0074)	(0.0080)
$Onset$	-0.0013	-0.0048	-0.0018	-0.0051
	(0.0026)	(0.0047)	(0.0019)	(0.0036)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0261	0.0191	0.0482	0.0658
Panel B: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0083*	0.0181**	-0.0024	0.0102***
	(0.0050)	(0.0075)	(0.0036)	(0.0038)
$Onset_M$	-0.0057**	0.0056**	-0.0036**	0.0040**
	(0.0024)	(0.0023)	(0.0017)	(0.0016)
$Onset_L$	-0.0031	-0.0068	-0.0047	-0.0022
	(0.0051)	(0.0065)	(0.0035)	(0.0037)
Panel C:	Downside Beta		Downside Volatility	
	(1)	(2)	(3)	(4)
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Fears$	-0.0079***	0.0070***	-0.0049**	0.0041**
	(0.0030)	(0.0027)	(0.0021)	(0.0018)
$Fears \times Onset$	-0.0187	0.0338*	-0.0057	0.0180**
	(0.0133)	(0.0181)	(0.0065)	(0.0091)
$Onset$	-0.0018	-0.0058	-0.0027	-0.0066
	(0.0028)	(0.0049)	(0.0018)	(0.0035)
$Controls$	Yes	Yes	Yes	Yes
Observations	1891	1890	1889	1889
R^2	0.0396	0.0285	0.0678	0.0853
Panel D: Test the Significance of Marginal Effect: $\beta_{fears} + \beta_{fears \times Onset} \times Onset$				
	Ret(t)	Ret[t+1,t+2]	Ret(t)	Ret[t+1,t+2]
$Onset_H$	-0.0159**	0.0214**	-0.0073**	0.0118***
	(0.0068)	(0.0089)	(0.0035)	(0.0044)
$Onset_M$	-0.0079***	0.0070***	-0.0049**	0.0041**
	(0.0030)	(0.0027)	(0.0021)	(0.0018)
$Onset_L$	6.91e-05	-0.0074	-0.0024	-0.0036
	(0.0060)	(0.0074)	(0.0034)	(0.0041)

This table links FEARS to daily high-minus-low return spreads on portfolios constructed by sorting on stock characteristics. We create decile portfolios, where high is defined as the value in the top decile and low is defined as the value in the bottom decile. Moreover, we show the estimates of simple slope. $Onset_H$, $Onset_M$ and $Onset_L$ are two standard deviations above $\overline{Onset}$, the mean of Onset, and two standard deviations below $\overline{Onset}$. The control variables include VIX, the CBOE volatility index; changes in EPU, the index of economic policy uncertainty; changes in Aruoba-Diebold-Scotti (ADS), the index tracks real business conditions; And lagged daily returns up to 5 lags. Standard errors are given in parentheses and they are corrected for White's (1980) heteroscedasticity and serial correlation up to 4 lags using the Newey-West (1987) estimator. The simple slope is $slope_{fears} = \beta_{fears} + \beta_{fears \times Onset} \times Onset$. Its standard error is given as $s_{slope} = (s_{fears} + 2 \times Onset \times s_{fears,Onset} + Onset^2 s_{Onset})^{\frac{1}{2}}$. *, ** and *** represent significance at the 10%, 5%, and 1% levels, respectively.